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Accuracy, robustness and comprehensibility – Challenges in bottom-up energy system models

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Abstract

This work provides a comprehensive framework for addressing key research gaps in bottom-up energy system modeling. While the field has experienced significant advancements in recent decades, largely due to improvements in computational capabilities and data availability, current models face persistent challenges in accuracy, robustness, and comprehensibility. While numerous review papers have examined specific aspects of energy system modeling challenges, no comprehensive framework exists that synthesizes all major challenges facing bottom-up energy system models under a unified structure. We propose a novel classification system that organizes these challenges into three fundamental categories, offering a structured approach to understanding and addressing them. Our conceptual framework, based on literature synthesis, proposes a thematic classification based on accuracy, robustness and comprehensibility as three pillars to map the challenges faced by bottom-up energy system models. For accuracy, we analyze the critical dimensions of temporal, spatial, techno-economic, and sector-coupling resolution, along with the importance of sector disaggregation. For robustness, we examine methods for addressing data-based and model-based uncertainties. For comprehensibility, we discuss the importance of transparency, participatory processes, behavior integration, environmental impact assessment, and multi-level modeling alignment. This holistic framework provides a roadmap of the overall challenges facing energy system models, equipping the field with a clearer path to close the persistent gap between modelling results and the concrete requirements of energy policy development and real-world energy transition implementation.

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1. Introduction

The definition and deployment of effective and efficient solutions and pathways to decarbonize the energy system rely on the ability of representing the performance of alternative technologies and options in a reliable and accurate way. In this framework, energy system models play a crucial role in supporting the exploration of future

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Abbreviations: CDR: Carbon Dioxide Removal, AI: Artificial Intelligence, DRO: Distributionally Robust Optimization, GIS: Geographical Information Systems, GSA: Global Sensitivity Analysis, LCA: Life Cycle Assessment, LDC: Load Duration Curves, MAUT: Multi-Attribute Utility Theory, MAVT: Multi-Attribute Value Theory, MCA: Monte Carlo Analysis, MCDA: Multiple Criteria Decision Aid, MGA: Modeling to Generate Alternatives, MILP: Mixed Integer Linear Programming, ML: Machine Learning, OpenMod: Open Energy Modelling Initiative, PCA: Principal Component Analysis, PROMETHEE: Preference Ranking Organization Method for Enrichment Evaluations, PyPSA: Python for Power System Analysis, RO: Robust Optimization, SES: Smart Energy System, S-LCA: Social Life Cycle Assessment, SP: Stochastic Programming, UC: Unit Commitment, UTA: UTilités Additives (Additive Utilities), VRES: Variable Renewable Energy Sources.

pathways to decarbonize the global energy system. The field of bottom-up energy system modeling has evolved significantly over the past five decades, beginning with early explorations in the 1970s triggered by the oil crises, which raised awareness of the need for energy system diversification and sustainability [1]. While computational capabilities have significantly improved in the last decade, allowing for more sophisticated and detailed energy system modeling, this advancement has been paralleled by an increasing complexity of the energy systems themselves. A major strand of this evolution has centered around 100% renewable energy systems, which have moved from being viewed as utopian to technically and economically feasible transition pathways [1]. These models increasingly emphasize cost optimization, sector coupling, storage integration, and the role of emerging technologies such as Power-to-X, hydrogen, and carbon dioxide removal (CDR) approaches. Despite methodological advances, remaining key research gaps need to be addressed to properly represent the complexities of the global energy transition. The objective of this contribution is to discuss and explore the main research gaps and challenges in bottom-up energy system modelling that must be bridged to close the persistent gap between modelling results and the concrete requirements of energy policy development and real-world energy transition implementation.

Energy system modeling is an approach used to analyze and evaluate different configurations and pathways for energy systems. It involves creating mathematical representations of energy supply, demand, and infrastructure to explore scenarios and support energy planning and policy decisions. As defined by Prina et al. [2], energy system frameworks are generalized modeling environments that can be applied to different case studies, while energy system models are specific applications of frameworks to particular cases with defined input data and assumptions. Models can be broadly categorized as either top-down or bottom-up approaches [3]. Top-down models take a macroeconomic perspective, representing the energy sector's interactions with the broader economy but with less technological detail. In contrast, bottom-up models provide a more detailed representation of specific energy technologies and infrastructure, allowing for the analysis of different technology options, but with less economic integration [3]. This paper focuses primarily on bottom-up energy system models and frameworks. Concrete examples of widely used bottom-up energy system frameworks include PyPSA [4], an open-source linear optimization framework capable of representing the European energy system [5] at high spatial and temporal resolution; EnergyPLAN [6], a user-friendly simulation-based tool specifically designed for hourly analysis of fully sector-coupled energy systems; Calliope [7], a multi-scale optimization framework designed for flexibility and transparency; and TIMES/MARKAL [8], a long-established optimization framework used by governments and research institutions worldwide for national and global energy scenario analysis. OSeMOSYS [9] and oemof [10], open-source optimization tools widely used for long-term national and regional energy planning; A comprehensive and regularly updated list of open-source energy system models and frameworks is maintained by the Open Energy Modelling Initiative [11].

It is important to note that the aim of this review paper is not to provide a detailed inventory of available models and their characteristics, this has been done comprehensively in several existing review papers (e.g., Ringkjøb et al. [12]; Chang et al. [13]; Samarasinghe et al. [14]), but rather to systematically map and discuss the methodological challenges that these bottom-up energy system models face as a class, regardless of the specific tool considered.

While numerous review papers have examined specific aspects of energy system modeling challenges (see Table 1), they have typically focused on particular subsets of these challenges, creating a fragmented landscape of knowledge in the field. This analysis addresses a critical gap by providing the first comprehensive synthesis that brings together all major challenges facing bottom-up energy system models. Unlike previous reviews that examine isolated aspects, this work aims to provide a comprehensive overview by not only synthesizing the full spectrum of challenges but also introducing a unified framework that serves as a systematic blueprint for bottom-up energy modelers. This holistic approach organizes and discusses these dimensions in a more structured manner, enabling researchers to understand interdependencies between different modeling challenges. Our framework focuses on enhancing models based on three fundamental principles: increasing their accuracy, strengthening their robustness, and improving their comprehensibility.

The urgency of addressing these modeling challenges is underscored by the critical role energy system models play in informing high-stakes policy decisions. These models directly influence national energy strategies, such as the European Green Deal's pathway to carbon neutrality [26], inform investment decisions worth billions of dollars in renewable energy infrastructure [27], and guide international climate commitments under the Paris Agreement [28]. When models lack accuracy, robustness, or comprehensibility, the resulting policy recommendations may be inaccurate [29] and suboptimal [30], leading to inefficient resource allocation, delayed decarbonization timelines [31], pathways that inadequately account for regional environmental impacts and material supply constraints, and reduced public acceptance of energy transition measures [32].

The limitations and challenges of existing energy system modeling frameworks have increasingly been addressed in the recent literature. Table 1 shows relevant review articles on the topic of bottom-up energy system modelling challenges. The need of both temporal and spatial resolution improvements is mentioned by all analyzed articles. This is fundamental to better represent variable renewable energy sources and flexible demand [33]. The need for improvements also about the resolution in techno-economic detail and the resolution in sector-coupling is also mentioned by several articles. The overarching challenge is to simultaneously increase resolution across all four dimensions [3]. Current modeling approaches are typically constrained to high resolution in a subset of dimensions, as computational limitations prevent simultaneous high-resolution representation across all four areas. Plazas-Niño et al. [20] debate how models should incorporate more detailed divisions of end-use sectors like buildings and industry to enable better representation of sector-specific technologies and efficiency options.

Several articles focus on the robustness challenge, with particular emphasis on assessing data-based uncertainties. Pfenninger et al. [33] highlight the importance of addressing uncertainty through methods like stochastic programming, Monte Carlo analysis, and scenario analysis. Yue et al. [34] provide a comprehensive framework identifying four distinct approaches: Monte Carlo Analysis, Stochastic Programming, robust optimization strategies, and Modeling to Generate Alternatives. Plazas-Niño et al. [20] specifically recommend incorporating uncertainty assessment methods like Monte Carlo simulation for handling inherent uncertainties in long-term energy modelling.

Fewer articles address structural or model-based uncertainty through comparing energy system frameworks, models, and scenario results. Prina et al. [2] analyze methods for framework comparison and evaluating the impact of different mathematical formulations on results. They emphasize that such comparisons require collaborative efforts between various institutions and harmonization of input data structures. Misconel et al. [35] and Ruhnau et al. [36] have conducted relevant work comparing high-resolution electricity system modeling approaches, though their focus remains primarily on the electricity sector rather than the entire energy system.

Table 1. Review articles addressing energy system modeling challenges.

		Increasing accuracy					Strengthening robustness		Improving comprehensibility				
Authors	**Year**	**Resolution in time**	**Resolution in space**	**Resolution in techno-economic detail**	**Resolution in sector-coupling**	**Increasing sector disaggregation and detail**	**Addressing data-based uncertainty**	**Addressing model-based uncertainty**	**Transparency and reproducibility**	**Participatory processes**	**Integrating human behavior and social factors**	**Integration of environmental impact assessment**	**Ensuring alignment in multi level modelling**
Pfenninger et al. [15]	2014	✓	✓				✓		✓	✓	✓		✓
Lopion et al. [16]	2018	✓	✓						✓		✓		
Ringkjøb et al. [12]	2018	✓	✓	✓	✓		✓		✓			✓	
Savvidis et al. [17]	2019	✓	✓	✓	✓		✓		✓		✓		
Groissböck [18]	2019	✓	✓	✓	✓		✓		✓				✓
Prina et al. [3]	2020	✓	✓	✓	✓		✓		✓		✓		
Fattahi et al. [19]	2020	✓	✓	✓	✓						✓		✓
Chang et al. [13]	2021	✓	✓	✓	✓				✓		✓		✓
Plazas-Nino et al. [20]	2022	✓	✓			✓	✓		✓		✓		
Fodstad et al. [21]	2022	✓	✓		✓		✓				✓		
Hofbauer et al. [22]	2022	✓	✓				✓		✓	✓			✓
Prina et al. [2]	2022	✓	✓					✓					
Laveneziana et al. [23]	2023	✓	✓	✓		✓	✓						
Hoffmann et al. [24]	2024	✓	✓	✓	✓		✓	✓	✓		✓	✓	
Samarasinghe et al. [25]	2024	✓	✓		✓		✓						

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Within comprehensibility challenges, transparency and reproducibility receive substantial attention. Pfenninger et al. [37] make a strong case for ensuring transparency of data and code, arguing it enhances regulatory and political acceptance. Groissböck [18] confirms that many open-source energy system models have comparable functionalities to proprietary tools. The challenges of integrating human behavior and social factors are examined by several authors, including Huckebrink and Bertsch [38], who critique the strong techno-economic focus of current models and their failure to adequately address behavioral complexity. Galster et al. [39] reveal that existing models predominantly focus on financial aspects while neglecting non-economic drivers of technology adoption.

Multi-level modelling refers to the coordination of energy system analyses across different governance scales, from continental and national down to regional and local levels, ensuring that model-based insights remain relevant and actionable for decision-makers at each level. The challenge of ensuring alignment in multi-level modelling is addressed by Hofbauer et al. [22], who provide a comprehensive review demonstrating that most models operate in isolation, focusing on a single governance scale while overlooking interconnections across municipal, state, and national levels. Less discussed in the literature are participatory processes and environmental impact assessment integration. McGookin et al. [40] present one of the few comprehensive frameworks for integrating stakeholders in energy system modeling, spanning research design through evaluation phases. For environmental impact assessment, Volkart et al. [41] demonstrate how coupling Life Cycle Assessment with energy system modelling can provide insights into multiple environmental impact categories, while Blanco et al. [42] showcase the benefits of this integration for assessing Power-to-Methane in the EU energy transition. These relatively understudied areas represent important opportunities for enhancing the comprehensibility and policy relevance of energy system models.

While these review articles provide valuable insights into specific aspects of energy system modeling challenges, a notable limitation emerges from this analysis (see Table 1): no single review comprehensively addresses all the identified challenges simultaneously. The existing literature tends to focus on particular subsets of challenges, temporal and spatial resolution, uncertainty assessment, or stakeholder engagement, without providing an integrated perspective on how these challenges interrelate. The present work fills this gap by introducing, for the first time, a unified three-pillar framework of accuracy, robustness, and comprehensibility that not only catalogs the full spectrum of challenges but explicitly maps their interdependencies. Rather than treating these challenges in isolation, the framework provides a structured approavch that enables researchers and practitioners to understand how progress in one pillar reinforces, and is constrained by, advances in the others, offering a systematic foundation for guiding future methodological development in bottom-up energy system modelling.

The remainder of this article is structured as follows. Section 2 presents the materials and methods used for the collection and analysis of the relevant literature base for this review. Section 3 constitutes the core of the paper and is divided into three sub-sections corresponding to the proposed framework pillars: increasing accuracy, strengthening robustness, and improving comprehensibility. Each sub-section is further subdivided to examine the specific challenges assigned to each pillar, providing detailed analysis of current approaches, limitations, and research directions. Finally, the conclusion section presents key findings, synthesizes the main insights from the framework analysis, and outlines directions for future research in bottom-up energy system modeling.

2. Materials and methods

This review employed a non-systematic integrative approach, combining elements of scoping, narrative, and umbrella review methodologies. This choice was deliberate: the field spans diverse methodological approaches, varying terminologies, and interdisciplinary contributions across engineering, economics, computer science, and policy studies, making rigid systematic inclusion criteria likely to exclude important contributions. The objective was not to quantitatively synthesize outcomes or test hypotheses, but to develop a comprehensive conceptual framework synthesizing knowledge across modeling challenges. The full literature search procedure is reported in Appendix A.

While the predominant trend in bottom-up energy system modeling has gravitated toward optimization-based linear programming approaches [43], the three-pillar framework of accuracy, robustness, and comprehensibility remains universally applicable across modeling paradigms. Agent-based models may inherently excel at comprehensibility challenges [44,45], while linear programming models have achieved high accuracy through resolution in time, space, techno-economic detail, and sector coupling [46], and system dynamics models offer superior capabilities for complex feedback loops [47]. Future research could benefit from framework-specific analyses that examine how each modeling paradigm addresses these universal challenges, potentially leading to hybrid approaches that leverage the strengths of multiple methodologies.

While this review aims to provide a comprehensive and structured overview of key challenges in bottom-up energy system modeling, it is important to acknowledge certain limitations. First, the classification and mapping of challenges reflect the authors' expert judgment and synthesis of the reviewed literature, and alternative categorizations may be equally valid depending on disciplinary perspective or modeling paradigm. Second, the framework intentionally emphasizes methodological and conceptual challenges rather than technical comparisons of individual models or tools, which would require a different scope and level of detail. Finally, we do not attempt to provide a quantitative prioritization of the identified challenges, as such prioritization would depend heavily on modeling context, research objectives, and available resources, an issue we propose as a topic for future review studies.

3. Bottom-up energy system modeling challenges

This section aims to synthesize the findings of the literature reviewed by mapping them onto three main general challenges: increasing accuracy, strengthening robustness, and improving comprehensibility. Fig 1 presents the results of this mapping exercise, providing a structured and concise overview of how the specific challenges highlighted in the literature align with the broader goals of accuracy, robustness, and comprehensibility. The next sections will address in detail these three domains of analysis.

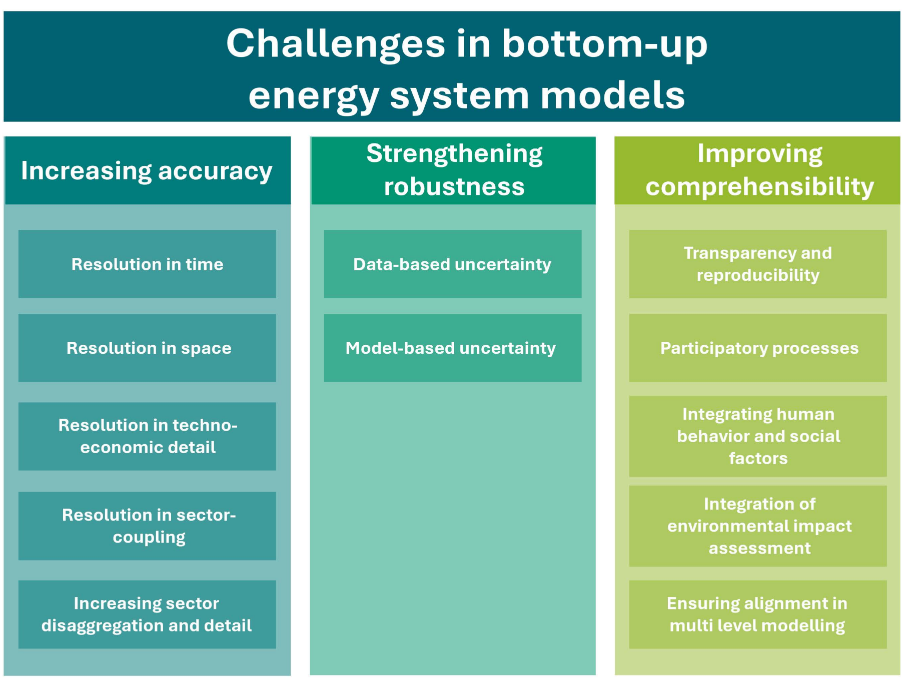

Fig 1. Mapping of the main challenges of bottom-up energy systems modelling.

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It is important to remark at this stage that this classification, aiming at being concise, may simplify some concepts by allocating them to a specific pillar although they may belong to more than one. The challenges grouped into the increasing accuracy goal are those that traditionally refer to the resolution techno-economic domains addressed by bottom-up energy system models. Although some additional aspects may develop further dimensions, such as social impacts or environmental impacts, they are not necessarily improve the accuracy of the model in representing the reality. Conversely, these challenges may help in making the model results easier to understand for the policy and decision makers, as they add further tools to read the results and connect them with relevant decision processes. For this reason, we have chosen to map these challenges into the third pillar, although we acknowledge that a different interpretation may be possible.

3.1. Increasing accuracy

Increasing accuracy is a crucial aspect of advancing energy system models to better represent the complexities of real-world energy systems. Accuracy in this context refers to the ability of models to capture the intricate details and dynamics of energy systems across multiple dimensions, enabling more accurate and reliable insights to support decision-making.

One of the primary challenges in increasing accuracy is improving the resolution of models, which refers to the level of detail captured in the models across various dimensions. Pfenninger et al. [33] highlight the importance of resolving time and space in models, as renewable energy sources are highly variable over time and their potential depends on the location. Increasing temporal resolution allows models to better represent supply and demand fluctuations, while higher spatial resolution enables a more accurate assessment of renewable potentials, costs, and transmission constraints. Prina et al. [3] further expand on this concept, proposing four key dimensions of resolution: time, space, techno-economic detail, and sector coupling. Techno-economic detail resolution refers to the level of technological and economic detail captured in the models. Low resolution in this dimension is characterized by simplified representations, such as modelling power plants as fully flexible with fixed efficiencies, omitting self-discharge in storage technologies, or using a fixed model configuration that does not allow users to vary the number of production units, storage systems, and energy demand. Conversely, high resolution in techno-economic detail involves more realistic representations, such as power plants with time-dependent ramp constraints, start-up costs, and part-load efficiencies, as well as the inclusion of primary, secondary, and tertiary reserves and prosumer models. Sector coupling resolution pertains to the level of integration between different energy sectors, such as electricity, heat, transport, and industry, in the models. Prina et al. [3] emphasize the importance of capturing the synergies and interconnections between these sectors, as demonstrated by the Smart Energy System concept developed by Lund et al. [6,48].

The concept of accuracy in energy system models is intrinsically linked to the resolution of the model itself. However, it is important to distinguish between accuracy and resolution, as these concepts are fundamentally different yet interconnected. Accuracy refers to the extent to which model results faithfully reproduce real-world behavior and outcomes, while resolution refers to the granularity at which the system is represented across temporal, spatial, techno-economic, and sectoral dimensions [3]. Increasing resolution can enhance accuracy by reducing model approximations and better capturing system dynamics, but it also increases computational time. Therefore, the objective is to find the optimal trade-off between accuracy and computational feasibility. Moreover, within resolution itself, there is a trade-off among different dimensions: maximizing resolution in one field while neglecting others may not yield optimal accuracy in final results. The challenge is to identify the optimal mix of resolutions across temporal, spatial, techno-economic, and sector-coupling dimensions that maximizes accuracy for an acceptable computational time. Research works confirm that a certain level of resolution can be sufficient to reach an acceptable accuracy, such as 60-min resolution data when dealing with variable renewables [49], and that an excessive level of complexity may indeed have a negative effect on the performance of the optimization model [50]. Furthermore, increasing resolution also requires that reliable data with that level of resolution is available for all the aspects that are modelled, as introducing approximations may nullify the effect of an increased resolution.

Poncelet et al. [51] investigated how lowering temporal and techno-economic detail resolutions affects the outcomes of bottom-up energy system models. The authors demonstrated the following concept: when improving model accuracy, increasing the time resolution should take precedence over adding more detailed technical and operational specifications. Jacobson et al. [52] used an electricity system planning model to quantify the impact of varying degrees of spatial, temporal, and techno-economic resolution. They concluded that while spatial resolution showed greater impact than temporal resolution in their analysis, this finding should not be generalized across all studies, but it is strongly connected to the chosen case study. Their key insight was that models are fundamentally limited by their lowest dimension of resolution, suggesting that balanced allocation of computational resources across all dimensions (spatial, temporal, and operational) is more important than maximizing any single aspect.

3.1.1. Resolution in time. The temporal resolution represents a fundamental aspect of energy system models' accuracy, that is of particular importance given the increasing penetration of variable renewable energy sources (VRES) in modern energy systems. The temporal structure in energy system models can be characterized by three key elements: the horizon (overall timeframe of analysis), periods (subdivisions of the horizon), and simulation year (specific year under analysis) [3]. For static or short-term models, the horizon typically coincides with a target year (e.g., 2030 or 2050) [53], while long-term models analyze entire transition pathways (e.g., 2020–2050) [3]. In long-term models, the horizon is often divided into periods of 2–5 years to reduce computational burden, with the simulation year being analyzed multiple times across these periods.

The temporal accuracy of a model is determined by its time-steps or time-slices - the intervals into which the simulation year is divided [54]. Traditionally, bottom-up energy system models have employed relatively coarse temporal representations, often using 12–32 time-slices per year (e.g., combinations of seasonal and daily divisions). This approach was historically adequate when energy systems were dominated by dispatchable fossil fuel and nuclear power plants with relatively constant output profiles. However, the increasing integration of VRES, storage systems, and demand-side management has created the need for higher temporal resolution to accurately capture several aspects, such as: generation variability from wind and solar resources, storage operation cycles, demand response and flexibility options, grid balancing requirements, VRES curtailment events. This creates a fundamental trade-off between model accuracy and computational efficiency. Higher temporal resolution provides a more precise representation of system dynamics but significantly increases computational requirements.

Research has shown that temporal resolution significantly impacts model outcomes, particularly in systems with high VRES penetration [2]. Deane et al. [55] showed how an energy system model adopting a low temporal resolution could underestimate VRES curtailments and overestimate the use of baseload plant. Haydt et al. [56] underlined the relevance of temporal resolution to avoid an overestimation of renewable resources in the planning of an energy system.

Various methodological approaches have emerged to balance accuracy and computational efficiency. While Pfenninger [57] (2017) categorized these approaches into downsampling, clustering, and heuristic selection, Marcy et al. [58] (2022) proposed a slightly different classification with sequential, categorical, and clustering methods. Though using different terminology, these classifications overlap significantly:

- Sequential or downsampling method. This technique simply averages sets of consecutive hours within specified intervals (e.g., every 2 hours or every 120 hours), but tends to perform poorly with data that has daily patterns like solar generation since it can average across multiple days.
- The categorical method described by Marcy [58] and the heuristic selection approach discussed by Pfenninger [57] both involve selecting representative periods. The categorical method selects profiles based on predefined categories (months, weekday/weekend), while heuristic selection targets specific criteria such as extreme events or maximum differences between demand and generation. Bistline [59] demonstrated that Representative Day approach can effectively capture the key characteristics of full hourly models while reducing computational complexity by an order of magnitude.
- Clustering method. This technique uses algorithms (like hierarchical clustering [60] or k-means clustering [61]) to group similar hours or days based on their characteristics, either focusing on individual parameters (like demand load, wind generation, or solar generation) separately or combining multiple criteria, creating clusters that capture similar temporal

patterns regardless of when they occur. A common application is Load Duration Curves (LDC), where hours are sorted from the highest to the lowest load value and then grouped into segments (e.g., top 1% of hours as one time-segment, next 4% as another, etc.), providing a simplified representation of system load patterns.

A comparison by Raventós and Bartels [62] (2020) of chronological versus coupling clustering methods found that chronological clustering of consecutive hours provided more predictable error convergence and better computational performance than coupling of independent days when modeling systems with significant storage capacity, though this advantage diminished for smaller networks. The chronological clustering method aggregates only consecutive hours of time series data, while coupling clustering groups data into representative days (maintaining daily patterns) while preserving storage unit states across the full time period using time-linking constraints for each hour of the year. Kotzur et al. [63] presents a comparative analysis of different time series clustering methods (averaging, k-means, k-medoids, hierarchical) found that medoid-based approaches outperformed centroid-based methods for energy system design optimization. A comparison by Teichgraeber and Brandt [64] (2019) analyzes conventional clustering methods (k-means, k-medoids, hierarchical) and shape-based methods (k-shape, dynamic time warping). Conventional methods compare time points directly, while shape-based methods look for similar patterns regardless of exact timing, making them potentially more suitable for capturing temporal variations in renewable energy and storage applications.

Kotzur et al. [65] (2018) demonstrate that traditional clustering approaches with independent typical periods cannot adequately model seasonal storage since they cannot exchange energy between periods. The authors propose an approach to handle seasonal storage in reduced temporal resolution models by introducing a two-layer state formulation that separates storage states into intra-period states (within typical periods) and inter-period states (between periods), allowing energy exchange between clustered periods.

Marcy et al. [58] demonstrated that multi-criteria clustering (combining load, solar, and wind profiles) achieved the lowest root-mean-square-error compared to other methods, while Pfenninger [60] concluded that no single method is universally optimal, though heuristic approaches showed particular promise, especially when modeling systems with high shares of renewable energy.

A critical yet often underappreciated challenge associated with temporal (and spatial) resolution is the identification of climate input data that are internally consistent across both temporal and spatial dimensions. Two broad approaches exist: historical reanalysis datasets and synthetically generated datasets. Reanalysis datasets, such as ERA5 [66] and MERRA-2 [67], are the most widely used sources for wind and solar generation time series, offering spatial consistency across nodes and long historical records essential for capturing inter-annual variability [68,69]. However, they reflect historical rather than future climate conditions, which becomes increasingly relevant for long-term scenarios. A particularly important class of events requiring careful treatment are Dunkelflaute events, prolonged periods of simultaneously low wind speeds and solar irradiance, whose occurrence may be underestimated when temporal resolution is reduced through clustering or downsampling methods [70,71]. Synthetic weather generators [72] and, more recently, machine learning-based generative models [73] offer alternatives for producing large ensembles of spatially consistent climate scenarios, though their validation against observed extremes remains an active research area [74,75]. In practice, the choice of climate data source should be guided by the modeling objective, and modelers should ensure consistency between the resolution of climate inputs and that of the energy system model to avoid systematic errors in the representation of renewable variability [76].

3.1.2. Resolution in space. The spatial resolution in energy system models refers to the geographical granularity at which energy systems are represented and analyzed. This dimension of resolution is particularly crucial for accurately capturing the spatial distribution of energy resources, infrastructure, and demand patterns. The spatial scope can range from individual buildings or districts to entire continents, with various levels of geographical disaggregation possible within each scope. The importance of spatial resolution has grown significantly with the increasing penetration of renewable energy sources, whose potential and performance are highly location-dependent. A review by Martinez-Gordon et al. [77] (2021) highlighted that higher spatial resolution has been proven highly beneficial for analyzing energy systems, particularly for systems with high penetration of variable renewable energy, as it enables a more accurate assessment of transmission grid bottlenecks, renewable energy potentials based on location, geographical variations in energy demand, and optimal infrastructure design/routing.

Frysztacki and Brown [78] (2020) studied the impact of different levels of spatial resolution (from 6 to 306 nodes) on the energy system modeling for Germany. They found that the optimal number of nodes to represent the historical curtailments of the power system is between 280 and 150 nodes, suggesting that a higher resolution isn't always better. This finding was primarily attributed to data quality challenges at high resolutions. While theoretically higher spatial resolution should provide more accurate results, this is only true if supported by correspondingly high-quality, granular data about grid connections, demand distribution, and infrastructure characteristics. The authors' findings suggest that model resolution should be matched to the reliability and granularity of available input data rather than maximized regardless of the data quality. Frysztacki et al. [79] (2021) studied the impact of different levels of spatial resolution (from 37 to 1024 nodes) on the energy system modeling for Europe using PyPSA-Eur [5]. They showed two competing effects: while higher resolution of renewable resource sites reduces system costs by up to 10% by allowing a better exploitation of high-quality locations, increased network resolution raises costs by up to 23% by revealing transmission bottlenecks that were previously hidden in more aggregated models. While theoretically higher spatial resolution improves the accuracy of results, the study demonstrates that this improvement is not linear with the increase in spatial resolution. For the European power system, the authors identified an optimal trade-off between accuracy and computational requirements at around 90 nodes for the power grid and 181 generation sites.

Models can be broadly categorized based on their spatial scope and resolution:

- Single-node models that treat the entire study area as one geographical point
- Multi-node models with distinct geographical zones connected by transmission links
- Highly resolved spatial models using detailed geographical information systems (GIS) data

The choice of spatial resolution involves important trade-offs. While higher spatial resolution can provide more accurate results, it significantly increases computational requirements and data needs. This creates a fundamental challenge in balancing accuracy with model tractability. Frysztacki et al. [80] (2022) investigated different clustering methods for spatial reduction in renewable electricity optimization models of Europe using the PyPSA-EUR model [81], an open-source optimisation model of the European transmission system built on the PyPSA framework [4]. They demonstrated that models with low spatial resolution, particularly those based on political borders such as countries, are inadequate as they neglect critical transmission bottlenecks and underestimate good generation sites for onshore renewables. When increasing spatial resolution to represent countries with multiple nodes, the method of spatial aggregation becomes crucial. For modeling highly renewable electricity systems, they recommend using hierarchical clustering that takes into account the network topology. Their analysis showed that simple clustering based on geographical coordinates alone produces less accurate results than hierarchical methods, both in terms of siting renewable capacities and estimating power flows.

An alternative approach combines capacity expansion optimization at medium spatial resolution with subsequent spatial disaggregation to higher resolutions. Spatial disaggregation methods aim to translate results from aggregated models into higher spatial resolutions while maintaining consistency and feasibility. Patil et al. [82] (2024) provide a systematic review of spatial disaggregation methods. In spatial disaggregation, source zones represent larger geographical units (like countries or states) containing known data values, while target zones are smaller units (like municipalities or grid cells) where values need to be estimated, with each target zone belonging exclusively to one source zone. Identified methods goes from the simplest areal weighting that distributes source zone values to target zones proportionally to their overlapping areas, assuming uniform distribution within each source zone to more complex techniques such as dasymetric mapping, proxy data-based methods, machine learning approaches that automatically determine complex relationships between multiple proxy variables and target data at the source zone level, then apply these learned relationships to predict values in target zones. Other complex methods are geostatistical models or hybrid methods that combine these approaches strategically - for example, using dasymetric mapping to establish initial boundaries, then applying machine learning within those boundaries to determine final values.

Frysztacki et al. [83] (2023) propose and compare three methods for disaggregation: uniform distribution which spreads aggregated capacities evenly across sub-regions while respecting land-use constraints, re-optimization based method which solves detailed local optimization problems within each aggregated region, Heuristic approaches - using simplified objectives or rules ("minimum excess electricity") to allocate capacities based on local conditions such as higher demand and grid capacity and thus to minimize load-shedding. They obtained that re-optimization produced the best results with lowest load shedding, and minimum excess electricity method performed nearly as well but with significantly lower computational cost, while uniform distribution showed the highest load shedding rates.

3.1.3. Resolution in techno-economic detail. The resolution in techno-economic detail, also called operational detail resolution [51], refers to the level of detail and accuracy with which technical constraints, operational characteristics, and economic parameters of energy system components are represented in the model [3]. This dimension of resolution has become increasingly important as energy systems grow more complex, particularly with the integration of variable renewable energy sources, storage technologies, higher cycling of conventional power plants and the need to accurately represent system flexibility. The concept of techno-economic detail resolution encompasses both technical aspects (such as operational constraints of power plants, storage characteristics, and system flexibility requirements) and economic parameters (including capital costs, operational costs, and maintenance expenses). At its core, this resolution determines how accurately a model can represent the real-world behavior and limitations of energy system components, which in turn affect the model's ability to produce realistic and implementable solutions. This aspect is specifically focusing on the technology, while the application of each technology across different sectors and applications has been considered in the following section on sector disaggregation and detail, where we consider specifically the role and characteristics of different uses of a given technology.

A model's resolution in techno-economic detail can range from simplified representations to highly detailed characterizations. Low resolution approaches might model power plants as perfectly flexible units with fixed efficiencies, use simplified storage models without self-discharge losses, or employ fixed system configurations that limit user flexibility in varying system components. In contrast, high resolution approaches incorporate detailed operational constraints such as minimum up and down times, startup and shutdown costs, part-load efficiency curves, and complex storage dynamics. The level of detail chosen has significant implications for both model accuracy and computational requirements, creating a fundamental trade-off that modelers must carefully consider. A systematic review by Oikonomou et al. [84] identifies three distinct approaches to representing thermal unit operations in power system models: binary variables for individual units, integer variables for aggregated similar units, and continuously relaxed variables. Their analysis shows how these choices reflect fundamental tradeoffs modelers face - binary variables provide the highest technical detail but greatest computational burden, while relaxed variables offer computational efficiency at the cost of reduced operational accuracy.

High resolution in techno-economic detail has been primarily explored through Unit Commitment (UC) models, which employ Mixed Integer Linear Programming (MILP) to incorporate detailed operational constraints of power plants [24]. These models typically focus on the electricity sector, optimizing generation to meet demand at minimum cost while considering crucial technical constraints such as ramp rates, partial load efficiency, and start-up costs. Several articles applied this approach: Shortt et al. [85] developed a MILP-based UC model to analyze the impacts of flexibility constraints across three distinct regions (Finland, Ireland, and Texas). Similar approaches were adopted by Palmintier et al. [86] for the ERCOT system in Texas, and further developed by Kirschen et al. [87], Belderbos et al. [88], Palmintier [89], Zhang et al. [90]. While these studies achieved high techno-economic resolution, their focus remained largely confined to the electricity sector due to computational limitations inherent in MILP formulations.

To address these computational challenges while maintaining detailed technical representations, researchers have explored various methodological approaches. One notable solution involves the use of integer clustering techniques in UC models. This technique works by grouping similar generating units with identical technical characteristics into clusters, treating them as a single aggregate unit while preserving their integer nature, thus significantly reducing the number of binary variables in the optimization problem without sacrificing the representation of key operational constraints [91]. However, even with these computational optimizations, most models remained focused on the electricity sector, overlooking potential flexibility benefits from sector coupling. Helistö et al. [92] demonstrated that the importance of operational detail resolution varies significantly based on system characteristics. Their study showed that while unit commitment constraints had significant impact in some systems, their importance could diminish in systems with high shares of variable renewable energy and widespread storage technologies. This finding emphasizes that the appropriate level of techno-economic detail may need to be tailored to the specific system under study. Helistö et al. [93] showed also that the impact of operational detail resolution is often less significant than improving temporal representation from a few representative periods to full chronological time series. Similar conclusions are also found by Poncelet et al. [51]. Another approach to address this computational problem came from Welsch et al. [94] and Deane et al. [55], who developed a soft-linking approach between UC models (using PLEXOS software) and long-term energy system models (TIMES).

3.1.4. Resolution in sector-coupling. As energy systems evolve toward higher renewable energy penetration, the integration and interaction between different energy sectors becomes increasingly critical. Resolution in sector-coupling refers to the model's ability to represent the interdependencies, synergies, and operational dynamics between different energy sectors - primarily electricity, heating, cooling, transport, and industry [3]. This dimension of resolution captures how precisely a model can simulate cross-sectoral energy flows, conversion processes, and flexibility options that emerge from sector integration. The concept builds on the Smart Energy System (SES) framework developed by Lund et al., which demonstrated how sector integration can increase system efficiency, enhance flexibility, and reduce overall costs in 100% renewable energy systems [95,96]. Connolly et al. [97], using this SES framework, have shown that achieving full renewable energy systems in Europe is technically feasible through sector coupling approaches. Mathiesen et al. [98] have also revealed that analyzing the power sector in isolation significantly underestimates the potential for variable renewable energy sources compared to integrated sector approaches. These studies were carried out using EnergyPLAN [6], a simulation-based tool specifically designed for the analysis of smart energy systems with high shares of renewable energy and strong sector coupling, and one of the most widely applied tools for national-scale integrated energy system analysis. Thellufsen et al. [99] have demonstrated that going beyond simple electrification-based sector coupling to utilize synergies between multiple energy grids (electricity, heating, cooling, and gas) can achieve both higher energy efficiency and lower costs compared to conventional approaches, particularly through the utilization of waste heat from industry, e-fuel production and power-to-heat. Brown et al. [100] further validated these benefits through modeling studies showing how sector-coupling technologies (using PyPSA-Eur [5]) like battery electric vehicles and power-to-gas can provide crucial flexibility in highly renewable European energy systems.

3.1.5. Increasing sector disaggregation and detail. The analysis of sector disaggregation and detail is seldom addressed on previous review papers, with some aspects described by Plazas-Nino et al. [20] and Laveneziana et al. [23]. However, the analysis of sector disaggregation represents another crucial dimension of model accuracy, as highlighted by Plazas-Niño et al. [11]. Increased sectoral detail allows models to better capture the specific characteristics, constraints, and opportunities for decarbonization within different end-use segments. This enhanced granularity is particularly important because different subsectors often have distinct energy consumption patterns, technical requirements, and potential pathways for emissions reduction. This is an additional dimension compared to the one already discussed about techno-economic detail, as in this case the focus is on the specific features of the end uses and applications and not on the characteristics of the technologies.

For example, in the building sector, disaggregating space heating consumption across different categories of building stock (e.g., by age, type, or energy performance [101]) enables models to evaluate targeted decarbonization measures such as facade insulation, roof improvements, basement insulation, or window replacements [102]. This granular approach helps identify the most cost-effective interventions for specific building segments rather than applying one-size-fits-all solutions.

Similarly, in the industrial sector, distinguishing between different energy use categories - such as direct electricity use, process heat at different temperature levels (low, medium, and high), and feedstock requirements [103] - allows for more precise modeling of sector-specific decarbonization options [104]. This detailed representation is crucial because technological solutions often have specific application domains: industrial heat pumps, for instance, are primarily suitable for low-temperature process heat applications, while other technologies may be required for high-temperature processes or feedstock uses [105].

Disaggregation is of particular importance in the transport sector, as each transport mode has specific characteristics and energy consumption drivers [106]. In addition, disaggregation in transport can also refer to other dimensions. Urban and rural mobility patterns are generally different both in terms of average distances and modal share [107], while the type of trips that are considered can be and additional feature: regular commuting trips and occasional leisure of business trips have different characteristics, and the users behave differently. Finally, other characteristics of vehicles and technologies can be usefully integrated in the models, such as the type of vehicles, fuels, age, size, segment [108].

This level of disaggregation, while computationally more demanding, enables models to better represent the technological and economic characteristics of different subsectors, leading to more realistic and actionable insights for policymaking. As noted by Plazas-Niño et al. [20], increasing sector disaggregation is particularly relevant as energy systems become more complex and integrated, requiring more detailed representation of end-use sectors to accurately model their interactions and potential for decarbonization. The optimal level of disaggregation should also be considered by taking into account the geographic and temporal resolution of the analysis, as an excessive level of disaggregation may also require additional assumptions to estimate model parameters that may not always be possible or reliable. Furthermore, as already described in the previous section, the level of disaggregation should also be chosen based on the computational effort that will be required to run the simulation or optimization model.

3.2. Strengthening robustness

Strengthening robustness is a fundamental requirement for energy system models that are intended to support high-stakes policy decisions. Robust results are those whose key conclusions remain valid across a plausible range of assumptions, input values, and modeling choices. Achieving robustness requires explicit attention to the diverse sources of uncertainty that pervade energy system modeling, from the data used to parameterize models to the structural choices embedded in their mathematical formulation.

Uncertainties in energy system modeling can be fundamentally divided according to the two main tasks that shape an energy model [109]. Data-based uncertainty arises from the process of collecting and quantifying information about the system under study. This category encompasses uncertainties related to parameter values, input data, and the characterization of system conditions, including technology costs, demand projections, renewable resource potentials, and climate variables. Model-based uncertainty stems from the representation of real-world systems through mathematical abstractions. This category includes uncertainties introduced through modeling choices, structural simplifications, and computational implementation, such as decisions about system boundaries, sector coverage, and mathematical formulation. These two categories are addressed in Sections 3.2.1 and 3.2.2 respectively, with the first one focusing on methods to characterize and address data-based uncertainty, and the second one addressing model-based uncertainty through framework, model, and scenario comparison.

3.2.1. Addressing data-based uncertainty. Data-based uncertainties arise from the process of collecting and quantifying information about the system under study and can be further classified into three subcategories. Aleatoric uncertainty, also termed stochastic or irreducible uncertainty, is caused by inherent variability or randomness in the system itself and cannot be reduced through additional knowledge or improved data collection [110,111]. Characteristic examples include variable production profiles of renewable energy sources that fluctuate with weather conditions, and variations in energy demand patterns due to behavioral factors or weather-dependent consumption [110]. Epistemic uncertainty results from imperfect or incomplete knowledge about the system and is, at least theoretically, reducible through additional research, measurement, or data collection. Typical examples include techno-economic parameters such as technology costs, efficiency values, resource potentials, and demand projections [112]. Deep uncertainty represents a qualitatively distinct category that arises when fundamental conditions prevent standard probabilistic characterization, for instance when key parameters cannot be described using conventional probability distributions due to lack of historical precedent, when multiple equally valid perspectives exist regarding what outcomes matter, or when future developments evolve in response to new information [113,114]. Energy transition modeling is particularly exposed to deep uncertainty given the unprecedented scale of transformation required, the long infrastructure lifetimes involved (30–50 + years), and fundamental stakeholder disagreements about objectives [115].

The challenge of addressing data-based uncertainty in energy system modeling is particularly relevant. Energy system models rely on numerous assumptions and input data that are inherently uncertain, which can significantly impact the reliability and robustness of the results [33]. According to Edenhofer et al. [116], these uncertainties span technological parameters, future costs of technologies (e.g., solar PV, batteries, electrolyzers), future fuel prices, climate-driven variations in energy demand, weather-dependent renewable energy generation potential, technology performance parameters, and demand elasticities and consumption patterns. When uncertainties are not properly considered, model outputs may lack the necessary robustness to serve as reliable guides for decision makers [34]. Yue et al. [34] identified four established approaches to address data-based uncertainty: Monte Carlo Analysis (MCA), Stochastic Programming (SP), robust optimization (RO) strategies, and Modeling to Generate Alternatives (MGA). These traditional uncertainty analysis methods are computationally intensive, often requiring thousands of model runs that can make comprehensive uncertainty assessment impractical for complex energy system models. Pfenninger et al. [33] highlight the importance of addressing uncertainty through such methods to hedge against unknown risks that models cannot predict. In this context, artificial intelligence (AI) and machine learning (ML) approaches have emerged as promising solutions, offering the ability to create computationally efficient surrogate models that can dramatically reduce the time required for uncertainty analysis while maintaining high accuracy. Guevara et al. [117] proposed an innovative framework combining machine learning and distributionally robust optimization (DRO), demonstrating that this hybrid approach can produce stable strategic investment decisions that are less sensitive to probability distribution assumptions while significantly reducing computational burden. Jahangiri et al. [118] demonstrated how deep neural networks used as surrogate models can analyze power system decarbonization pathways across thousands of scenarios, revealing robust features of transition pathways while identifying key variables that shape divergent outcomes. Prina et al. [119] showed that a neural network surrogate of EPLANopt [120], an optimization wrapper built on EnergyPLAN [6], achieved a relevant reduction in computational time, enabling more extensive uncertainty and scenario exploration than previously feasible with traditional methods.

A complementary and often underutilized approach is the systematic characterization of input uncertainty through global sensitivity analysis (GSA). While MCA and SP propagate uncertainty through the model, GSA goes further by identifying which input parameters are most influential in driving output variability, a critical step for prioritizing data collection efforts and model validation. Variance-based methods, such as Sobol indices, decompose output variance into contributions from individual inputs and their interactions, providing a rigorous ranking of input importance [121]. Applied to energy system optimization models, GSA has shown that demand levels and technology costs are typically the dominant drivers of output uncertainty in decarbonization scenarios, while other parameters, such as certain efficiency values, contribute comparatively little [121]. This type of analysis can directly guide modelers in focusing uncertainty treatment where it matters most, rather than applying computationally expensive methods uniformly across all inputs. Computationally, ML-based surrogate models play a dual role here: they not only accelerate uncertainty propagation but also enable GSA at scales that would otherwise be infeasible [122].

Technology cost uncertainty represents one of the most consequential sources of input uncertainty in long-term energy models, as cost projections for solar, wind, batteries, and electrolyzers diverge significantly across sources and time horizons. Duan and Caldeira [123] demonstrated that differences in technology cost projections can substantially alter the optimal technology mix in decarbonized electricity systems, underscoring the need to treat cost inputs probabilistically rather than as fixed point estimates. Similarly, inter-node interactions and sectoral demand projections, highlighted by the reviewer as critical dimensions of input uncertainty, require explicit treatment, as a highly detailed model with inconsistent or uncertain inputs may still yield unreliable results regardless of its resolution. Climate-driven input uncertainty, affecting renewable generation potential, heating and cooling demand, and hydropower availability, represents a further critical dimension that has received growing attention. Plaga and Bertsch [112] provide a systematic review of methods for assessing climate uncertainty in energy system models, identifying scenario analysis, stochastic optimization, and sensitivity analysis as the main approaches, each with distinct computational requirements and suitability for different modeling contexts.

A further methodological direction to address deep uncertainty in long-term planning is multi-stage modeling, which extends rolling horizon approaches by distinguishing between short-term operational commitments and long-term planning flexibility. Unlike stochastic programming, which relies on well-defined probability functions, multi-stage frameworks can handle cases where future conditions, such as demand trajectories, are subject to forecast revisions rather than known probability distributions. Recent work has proposed multi-stage modeling frameworks that explicitly represent decision-making under imperfect foresight, where investment decisions are made based on forecasted expectations but revised as new information becomes available over the planning horizon, an approach shown to more realistically replicate historical capacity development compared to conventional perfect foresight models [109].

3.2.2. Addressing model-based uncertainty. Model-based uncertainties stem from representing real-world systems through mathematical abstractions and can be classified into three subcategories. Boundary uncertainty arises from decisions regarding which system components, sectors, or interactions to include in the model scope and which to exclude or aggregate, involving trade-offs between model tractability and representational completeness, such as choices regarding temporal resolution, spatial granularity, sectoral coverage, and technological disaggregation. Structural uncertainty stems from the approximations and simplifications inherent in representing real-world processes through mathematical equations, manifesting in choices such as simplified supply-demand balances versus detailed thermodynamic models, linearizing non-linear processes, assuming perfect foresight versus myopic decision-making, or employing aggregated versus unit-level technology representations. Technical uncertainty arises from computational and implementation aspects including numerical solution methods, optimization solver selection and configuration, programming implementation, and discretization approaches, where different solvers may employ distinct algorithmic approaches and converge to different solutions, particularly for non-convex problems.

The comparison of energy system frameworks, models, and scenario results is another significant challenge in the research area of energy system modeling. Addressing this challenge is crucial for adding robustness to the modelling results and ensuring the technical feasibility of the identified transition pathways [2]. The comparison of energy system frameworks involves evaluating the impact of different mathematical formulations on the final results. It is therefore possible to classify it as structural uncertainty. This requires collaborative efforts between various institutions that develop different frameworks and the harmonization of input data structures across multiple frameworks. Conducting comparisons using a large sample of frameworks and applying advanced statistical techniques and clustering analyses is beneficial for understanding the deviations between framework results. For this reason, the comparison of energy system frameworks has gained momentum only through recent research initiatives, with dedicated projects emerging in Germany [124] and the European Union [125], alongside collaborative efforts through modeling forums established in the US [126], Canada [127], China [128] and Europe [129].

Framework comparison studies predominantly employ quantitative approaches [2], focusing on metrics such as energy generation mixes, CO_2 emissions, and system costs [35,36,130]. More sophisticated quantitative approaches have emerged, incorporating statistical analyses and clustering techniques. For instance, Bistline et al. [131] analyzed 16 frameworks using median and average calculations, while Gils et al. [132] developed clustering algorithms to identify systematic deviations across nine frameworks. Most existing studies focus solely on the electricity sector [35,36,130], with only a few examining all energy sectors comprehensively. Notable exceptions include Gils et al. [133], who compared four frameworks across all sectors, and Herc et al. [134], who conducted a comprehensive sector analysis. While hourly generation profiles and computational process indicators are available for comparison, they are less frequently utilized [35,135]. Recent studies have demonstrated the value of advanced statistical analysis in framework comparison, particularly when examining larger samples. For example, Gils et al. [136] employed box plots, median calculations, and quartile analysis across eight frameworks, while Giarola et al. [137] evaluated power generation deviations to assess energy storage integration impacts.

The comparison of energy system models is performed to examine the impact of different levels of resolution (time, space, techno-economic detail, and sector coupling) on the final results [2] and can be classified as boundary uncertainty. No existing study has simultaneously examined the effect of varying all four resolution fields through model comparisons. Assessing the approximations introduced by lowering resolution in each field, as well as the associated computational benefits, is an important challenge. Providing guidance on prioritizing different resolution fields to maximize accuracy at reasonable computational costs is a key need in the energy system modelling research field.

Models are typically evaluated based on economic and energy-related indicators, with cost deviation metrics being the most frequently employed [50,65,138]. Several mathematical approaches have been developed to assess these deviations, including system cost deviation [138], objective function value deviation [50], and levelized cost of electricity deviation [57]. A notable innovation is the misallocation metric introduced by Schyska et al. [139], which eliminates the need for a reference model in expansion capacity optimization comparisons. Other key performance indicators include generation mix error [51], installed capacities [140,141], and computational process indicators [62,57,142]. Model comparisons primarily examine the impact of different resolution levels on results, focusing on the above-mentioned four key dimensions: temporal, spatial, techno-economic detail, and sector coupling. Most studies concentrate on temporal resolution [56,60,62–64,143–145], with fewer addressing both temporal and techno-economic detail [94,51,140,55]. Some researchers have explored multiple resolution fields simultaneously, such as Priesmann et al. [50], who examined temporal, spatial, and techno-economic aspects, though no study has yet analyzed all four resolution fields together.

The comparison of energy system scenario results allows identifying the similarities and areas of disagreement between the results obtained from different frameworks and models. Unlike framework and model comparisons, scenario results comparison can encompass a substantially larger number of cases due to reduced requirements for data harmonization and model alignment. While most studies focus exclusively on the electricity sector, with notable examples including multi-country analyses [146,147], only limited research, such as Naegler et al. [148], has examined scenarios incorporating comprehensive sector coupling. Literature reveals a strong preference for quantitative analysis methods, with particular emphasis on energy-related metrics. These typically include comparative analyses of generation patterns, demand profiles, and infrastructure capacity requirements, while economic and environmental indicators receive comparatively less attention. Several studies have implemented more advanced quantitative methodologies. These include Densing et al. [149], who employed principal component analysis (PCA) to reduce dimensionality and squared Euclidian distance calculations to assess scenario variations. Lunz et al. [150] developed a novel approach using residual load recalculation algorithms to standardize scenarios for CO_2 emission reduction comparisons. In examining storage requirements, Cebulla et al. [151] utilized linear interpolation techniques to evaluate scenarios dominated by different renewable energy sources. A comprehensive statistical approach was demonstrated by Thimet et al. [152], who analyzed power sector scenarios across multiple European countries using median and quartile analysis to evaluate generation mix variations and demand deviations from baseline values.

3.3. Improving comprehensibility

Chang et al. [13] highlight the importance of strengthening the policy relevance of energy system modelling tools. They argue that a crucial aspect of energy system modelling is the ability to quantify the impacts of changes in the energy system and contribute to the public debate, while also supporting decisions to guide the energy transition [13]. The authors note that while the technical features of some energy modelling tools enable the analysis of policy-relevant questions, the actual use of these tools to support official (government) policy is more limited. In their survey of 54 modelling tools, they found that while many tools have been used for policy support, either directly or indirectly as a reference, over a third of the surveyed models did not have any identifiable policy contribution [13]. This suggests a gap between modelling efforts and their policy applications, potentially due to a lack of awareness or involvement of policymakers in discussing modelling features and results. The authors emphasize the importance of involving policymakers in discussions about modelling tools and their outcomes, as it could enrich the end-use of energy system models and produce scenarios that better answer policy-related questions. The following sections will describe the different dimensions that are associated with improving comprehensibility of energy system modeling.

3.3.1. Transparency and reproducibility. Pfenninger et al. [37] highlight the importance of ensuring transparency of data and code as a crucial challenge in energy system modeling. They argue that transparent modeling is desirable from a regulatory and political perspective, as opening up decision processes and the reasoning behind them may lessen public opposition to new legislation and infrastructure [37]. The authors emphasize the need for increased transparency and reproducibility, which can be achieved by making model code and data publicly available. They state that "when insight gained from models is used to design public policy, the models should be transparent and accessible to a degree where independent review is possible" [37]. However, they acknowledge the challenges researchers face, such as the time and effort required for documentation and maintenance of publicly accessible databases, as well as concerns about protecting proprietary knowledge and commercial data.

The concept of transparency and reproducibility is also tightly linked with open data and open source approaches. A significant example in the energy modelling domain is the OpenMod initiative [153]. OpenMod brings together energy modelers from different international institutions with the aim of supporting open science and promoting "the idea and practice of open energy modelling among fellow modelers, research institutions, funding bodies, and recipients of their work". This network of researchers is a way to exchange ideas and source code, lobby for policy support for open projects, and actively share data, code and knowhow within the community.

A review by Groissböck [18] confirms that many open source energy system models have similar functionalities compared to commercial or proprietary tools of serious use, thus making them suitable to be used for the same applications and analyses.

Berendes et al. [154] have specifically addressed the usability of open source frameworks as energy system models, to evaluate the effectiveness of these solutions, although limiting their scope to the developer perspective. Their findings suggest possible areas of improvement in handling input data and error messages, and they plan to further improve their results by extending the analysis to a broader range of users.

3.3.2. Participatory processes. The challenge of improving participatory processes in energy system modeling is also particularly relevant, as highlighted by McGookin et al. [40]. The authors emphasize the importance of involving a diverse range of stakeholders and the public in the energy system modeling process to ensure that the resultant policy decisions are fairer and better reflect people's concerns and preferences. The authors argue that while there is a growing awareness of the relevance of engaging stakeholders in the modeling process to ensure transparency, trust, and policy impact, stakeholders and the public are still largely excluded or their engagement is limited to the beginning or end of the modelling process [155,156]. Collaborative co-creation energy systems modelling approaches, where stakeholders are involved throughout the process, are an exception.

Trutnevyte et al. [157] (2011) demonstrated through their case study in Urnäsch, Switzerland, that involving stakeholders throughout the modeling process and combining both intuitive and analytical approaches to vision assessment led to more informed preferences and better capacity building for local energy transitions. Marinakis et al. [158] (2017) further show through their analysis of local energy planning in Greece that participatory multi-criteria frameworks help evaluate alternative scenarios for sustainable energy action plans, allowing stakeholders to systematically assess different implementation pathways while considering environmental, social and economic impacts. McKenna et al. [159] (2018) showed that integrating participatory approaches with energy system optimization models and multi-criteria decision analysis in German municipalities helped overcome barriers in smaller communities that typically lack technical and administrative resources for sustainable energy planning. Simoes et al. [160] (2019) demonstrated through case studies in four European cities that combining quantitative energy system modeling with stakeholder-driven multi-criteria analysis led to more realistic and feasible selection of sustainable energy measures compared to using modeling results alone. Höfer et al. [161] (2020) used Value-Focused Thinking combined with Multi-Attribute Utility Theory (MAUT) in their participatory evaluation of energy transition scenarios in Germany, showing that involving stakeholders in every step of the decision process, from formulating scenarios to weighting criteria, helps identify key policy recommendations based on distinct stakeholder perspectives.

Most of the papers in this topic implement Multiple Criteria Decision Aid (MCDA) methods because they provide a systematic framework for incorporating multiple, often conflicting objectives and stakeholder preferences into the decision-making process, while helping to structure and make transparent the complex trade-offs inherent in energy system planning decisions, such as balancing environmental impacts with economic costs, or technical feasibility with social acceptance. Regarding the MCDA methods employed, Trutnevyte et al. [157] implemented a Multi-Attribute Value Theory (MAVT) with weighted sum aggregation, Marinakis et al. [158] combined the UTA II (UTilités Additives) Method combined with extreme ranking analysis, McKenna et al. [159] employed MAVT with swing weighting for criteria weights elicitation and weighted sum aggregation, Simoes et al. [160] applied the PROMETHEE method with a two-step consensus building process for stakeholder criteria weighting.

McGookin et al. [40] (2024) provide comprehensive guidance for integrating stakeholders in energy systems modeling, outlining a framework that spans research design, model development, results analysis, communication, and evaluation phases, while emphasizing good practice principles such as stakeholder mapping, flexible approaches, acknowledgment of model limitations, and respect for diverse perspectives.

An innovative approach presented by Lombardi and Pfenninger [162] introduce an innovative "human-in-the-loop" approach by combining modeling to generate alternatives and stakeholders preferences that automatically translates stakeholder preferences into model parameters, enabling the generation of design alternatives that better align with stakeholder needs while facilitating consensus-building in energy planning decisions. Vågerö et al. [163] describe a novel participatory modelling approach using near-optimal energy system alternatives to involve stakeholders in energy planning decisions in Longyearbyen, Norway, similar to Lombardi and Pfenninger's human-in-the-loop methodology, but using an interactive interface that allows citizens to explore a continuum of feasible energy system designs and make trade-offs between various priorities like emissions, costs, and vulnerability.

Another emerging aspect of improving the policy relevance and comprehensibility of energy system models, particularly in participatory contexts, is the more detailed representation of policy instruments. Participatory modeling processes often involve diverse stakeholders, including policymakers, industry representatives, NGOs, and citizen groups, each of whom may bring specific perspectives on the feasibility, acceptability, and impacts of different policy tools. However, when models rely exclusively on abstract instruments like carbon pricing, they may fail to capture the nuances and trade-offs associated with the actual policy options under consideration. Historically, many models have used carbon pricing as a proxy for policy action [164,165]; however, it is increasingly recognized that different instruments, such as renewable portfolio standards, technology-specific subsidies, regulatory bans, and feed-in tariffs, can lead to divergent system behaviors and investment patterns [166]. Accurately representing these instruments helps align model outputs with real-world policymaking processes and enhances stakeholder engagement by enabling more grounded comparisons of policy options.

3.3.3. Integrating human behavior and social factors. The challenge of integrating human behavior and social factors also falls under the "Improving Comprehensibility" category. Galster et al. [39] have analyzed in a review paper how different energy system models integrate behavioral drivers of technology adoption and energy service use. Their findings reveal that existing models have a predominant focus on financial aspects, while non-economic drivers are lacking. They also suggest strategies to support a better integration of social sciences within these models, to reach interdisciplinary projects that can lead to results with a better accuracy. Huckebrink and Bertsch [38] argue that while energy system models have a strong techno-economic focus, they often fail to adequately address and consider the complexity of human behavior related to acceptance, adoption, and use of energy technologies. They emphasize the importance of integrating human behavior and social factors into energy system models to improve their capabilities in producing more reliable results and informing policymakers about societally feasible pathways for transforming the energy system. Failing to account for these factors can lead to scenarios and transition pathways that may face significant societal barriers and challenges in real-world implementation. However, as pointed out by Egner [167], successfully integrating behavioral science in energy system modelling and forecast is hard and complex, and it is not possible to perfectly predict users' behavior. The author highlights the importance of involving behavioral researchers in the project to manage the complexity of this dimension, due to the different behavioral theories available and the multiple aspects that need to be taken into account. Ball-Burack et al. [168] confirm that current models tend to oversimplify technology adoption decision, as they focus on homogenized financial factors while neglecting consumer heterogeneity and non-monetary influences.

Nevertheless, some researchers propose methodologies to integrate some socio-technical and socio-political behaviors in energy system modeling. Verrier et al. [169] provide recommendations on incorporating social mechanisms of change within energy analysis. These mechanisms include resistance to change and the diffusion of environmental values, and the authors evaluate them in the framework of a probabilistic energy system model, considering people's attitudes towards building heating technologies in the UK. Fisch-Romito et al. [170] underline the importance of performing a systematic and transparent selection of the most important social factors that should be integrated into energy system modeling. Their findings, based on an analysis of several European countries, confirm that the integration of social factors improve the modelling of pathways for energy transition, with the most important aspect being public acceptance, investment risks and infrastructure lock-in.

It is important to note that different modeling methodologies face varying degrees of difficulty in integrating social aspects into energy system analysis. While linear programming centralized optimization models encounter significant challenges in implementing social factors due to their mathematical structure and focus on cost minimization [171,172], agent-based models may inherently excel at addressing these comprehensibility challenges, particularly in integrating human behavior and social factors [44,45]. Agent-based modeling approaches allow for explicit representation of heterogeneous decision-making processes, social interactions, and bounded rationality [173] that are difficult to capture in optimization frameworks, making them particularly well-suited for exploring the social dimensions of energy transitions and technology adoption dynamics [174].

3.3.4. Integration of environmental impact assessment. Another important challenge in Improving Comprehensibility of energy system models is the integration of environmental impact assessment, particularly through the incorporation of Life Cycle Assessment (LCA) methodology. LCA is a well-established approach for evaluating the environmental impacts of products, processes, and systems throughout their entire life cycle, from raw material extraction to end-of-life disposal [175]. By integrating LCA into energy system models, researchers can comprehensively assess the environmental implications of different energy technologies and transition pathways, considering factors such as greenhouse gas emissions, particular matter, ozone layer depletion, acidification, land use, resource use, and ecosystem impacts [176]. Incorporating LCA into energy system models enables decision-makers to identify potential trade-offs and synergies between different environmental objectives, as well as to compare the life-cycle environmental performance of alternative energy technologies and scenarios [177]. Volkart et al. [41] demonstrate how coupling LCA with energy system modelling can provide insights into the environmental impacts of future energy scenarios across multiple categories, such as climate change, water depletion, and land occupation. Similarly, Blanco et al. [42] showcase the benefits of integrating

LCA and energy system modelling to assess the environmental implications of Power-to-Methane in the EU energy transition, considering 18 impact categories.

However, integrating LCA into energy system models poses methodological and computational challenges, such as ensuring consistency in system boundaries, dealing with data uncertainties, and managing the increased complexity of the resulting models [178]. Blanco et al. [42] discuss issues like double-counting, temporal and spatial differentiation, and the need to harmonize data between the energy system model and LCA databases. Volkart et al. [41] also highlight the importance of data quality and the challenges of representing future technologies in LCA. Overcoming these challenges is crucial for improving the accuracy and comprehensiveness of energy system models in capturing the diverse environmental dimensions of the energy transition.

Many studies are now incorporating also the social dimensions in their impact assessments, through the social life cycle assessment (S-LCA) methodology. This approach aims to go beyond the classical analysis of environmental impacts of the LCA, by also considering additional dimensions that are relevant to the development of effective policies and strategies to improve the quality of energy systems. S-LCA is being applied to multiple sectors, such as the analysis of alternative mobility scenarios to decarbonize transport systems [179], or the comparison of electricity generation from renewable sources with conventional fossil fuels [180]. However, S-LCA remains a relatively new methodology, and in many cases the social impacts included in the analyses of energy systems mostly focus on employment, GDP or health and safety issues. Few studies in the literature present a rigorous approach to account for social impacts affecting different stakeholder categories [181].

3.3.5. Ensuring alignment in multi-level modeling. Multi-level modeling represents a crucial approach to bridge the gap between different spatial scales in energy system analysis, enabling coherent policy recommendations across continental, national, regional, and local levels. Multi-level modeling refers to the practice of ensuring consistency and alignment between energy system models operating at different geographical scales, from continental or global down to local community levels. This approach recognizes that energy transitions require coordinated action across all governance scales, and that model-based insights must be relevant and applicable to decision-makers at each level.

It's worth noting that most energy system modeling studies and academic articles focus predominantly on the national level [22], with corresponding policy recommendations targeted at national decision-makers. However, the actual implementation of energy transition measures is largely carried out by regional and local authorities who often lack the tailored modelling insights needed for effective action. Hofbauer et al. [22] present a comprehensive review of 186 energy modeling studies, demonstrating that most models operate in isolation, focusing on a single governance scale while overlooking the interconnected nature of energy decision-making across municipal, state, and national levels. The authors identify that only a small fraction of energy models explicitly incorporate scenarios that address characteristics or developments from other governance scales, and even fewer integrate actual strategies and policies from actors at different levels. This siloed approach fails to facilitate the coordination necessary for effective energy transitions, which require concerted action across governance scales.

Some state-of-the-art models such as PyPSA [182] and its European implementation PyPSA-Eur [5] represent state-of-the-art examples of high spatial resolution continental modelling, with Neumann et al. [183] demonstrating their application to hydrogen network planning across Europe at fine spatial granularity. In principle, the most comprehensive approach would be to develop a single model with extremely high spatial granularity covering continental areas, thus naturally ensuring alignment across scales. However, this approach faces significant computational limitations, particularly for complex models that incorporate high temporal resolution, detailed techno-economic constraints, and sector coupling. As model complexity increases in these dimensions, the computational requirements for maintaining fine spatial detail across a continent become prohibitive.

To address this challenge, various methods have emerged for ensuring alignment between models at different scales. One prominent approach utilizes spatial disaggregation methods, which allow modelers to translate results from larger-scale models to smaller geographical units. As discussed earlier in Section 2.1.2, these methods range from simple areal weighting to more sophisticated techniques that incorporate proxy variables, machine learning, or optimization-based approaches.

4. Conclusions

Energy system models serve as critical tools for navigating the global transition toward sustainable energy systems and mitigating climate change. This work addresses the fragmented landscape of challenges identified in existing energy system modeling literature by providing a holistic framework that systematically organizes these challenges into three fundamental pillars: increasing accuracy, strengthening robustness, and improving comprehensibility. The challenges have been mapped in the most significant pillar, although some of them show aspects that could extend to more than one pillar.

Increasing the accuracy of energy system models is essential for capturing the complexities of real-world energy systems. This requires advancing resolution across four key dimensions: temporal, spatial, techno-economic detail, and sector coupling. While current models excel in one or two dimensions, the primary challenge lies in simultaneously achieving high resolution across all dimensions without exceeding computational limitations. Additionally, increasing sector disaggregation, particularly in buildings, industry, and transport, enables more precise modeling of technology options and decarbonization pathways for specific subsectors.

Strengthening robustness involves effectively addressing uncertainties inherent in energy system models. Methods such as Monte Carlo analysis, stochastic programming, robust optimization, and modeling to generate alternatives offer valuable approaches for handling both data-based and model-based uncertainties. Emerging artificial intelligence and machine learning techniques show promise in creating computationally efficient surrogate models that significantly reduce the time required for uncertainty analysis. Furthermore, a systematic comparison of energy system frameworks, models, and scenario results adds critical layers of validation and insight, though harmonizing inputs across multiple frameworks remains challenging.

Improving comprehensibility focuses on enhancing the accessibility and policy relevance of model outputs. This includes increasing transparency and reproducibility through open data and open-source approaches, implementing participatory processes that engage stakeholders throughout the modeling process, integrating human behavior and social factors, incorporating environmental and social impact assessments through life cycle methodologies, and ensuring alignment across multi-level modeling from continental to local scales.

Addressing these challenges is important for advancing energy system modeling and strengthening its contribution to effective policy decision-making. By developing models that more accurately capture system complexities, robustly address uncertainties, and effectively communicate insights to stakeholders, the field can better support the complex planning and implementation of global energy transitions and decarbonization efforts.

For researchers, the three-pillar organization aims to provide a clear roadmap of the overall challenges facing energy system models and maps the current state-of-the-art alongside innovative methods for addressing specific issues within each pillar. By clearly delineating the relationships between accuracy, robustness, and comprehensibility challenges, the framework guides researchers toward developing novel approaches that address multiple dimensions simultaneously rather than focusing on isolated improvements.

While some discussion on the prioritization of challenges has emerged, particularly within the accuracy domain, where works such as Jacobson et al. [52] have emphasized that models are fundamentally limited by their lowest-dimension resolution and advocate for a balanced allocation of computational resources across dimensions, developing a clear and comprehensive prioritization across all identified challenge fields and specific issues remains extremely difficult and context-dependent, and should be considered a key objective for future research and review studies on the challenges of energy system models.

4.1. Appendix A

Literature identification followed a multi-pronged approach. Database searches were conducted in Scopus, Web of Science, and Google Scholar using the following primary search string:

(“energy system model*” OR “energy system framework*” OR “bottom-up energy model*”) AND (“challenge*” OR “limitation*” OR “accuracy” OR “robustness” OR “uncertainty” OR “temporal resolution” OR “spatial resolution” OR “sector coupling” OR “comprehensibility” OR “transparency” OR “stakeholder*” OR “multi-level model*”)

Additional targeted queries covered energy model comparison, stochastic and robust optimization methods, participatory modeling, life cycle assessment integration, and behavioral aspects of energy modeling. These database searches (n = 981) were complemented by citation tracking and expert knowledge of the field (n = 50), yielding 1031 records in total. After removal of duplicates, 722 records were screened by title and abstract; 464 were excluded as clearly outside the scope of bottom-up energy system modeling. The remaining 258 sources were assessed in full text, of which 91 were excluded (focused exclusively on top-down macroeconomic models; or not relevant to any of the three framework pillars), leaving 182 sources included in the review. The full selection process is reported in Fig 2 and in S1 File.

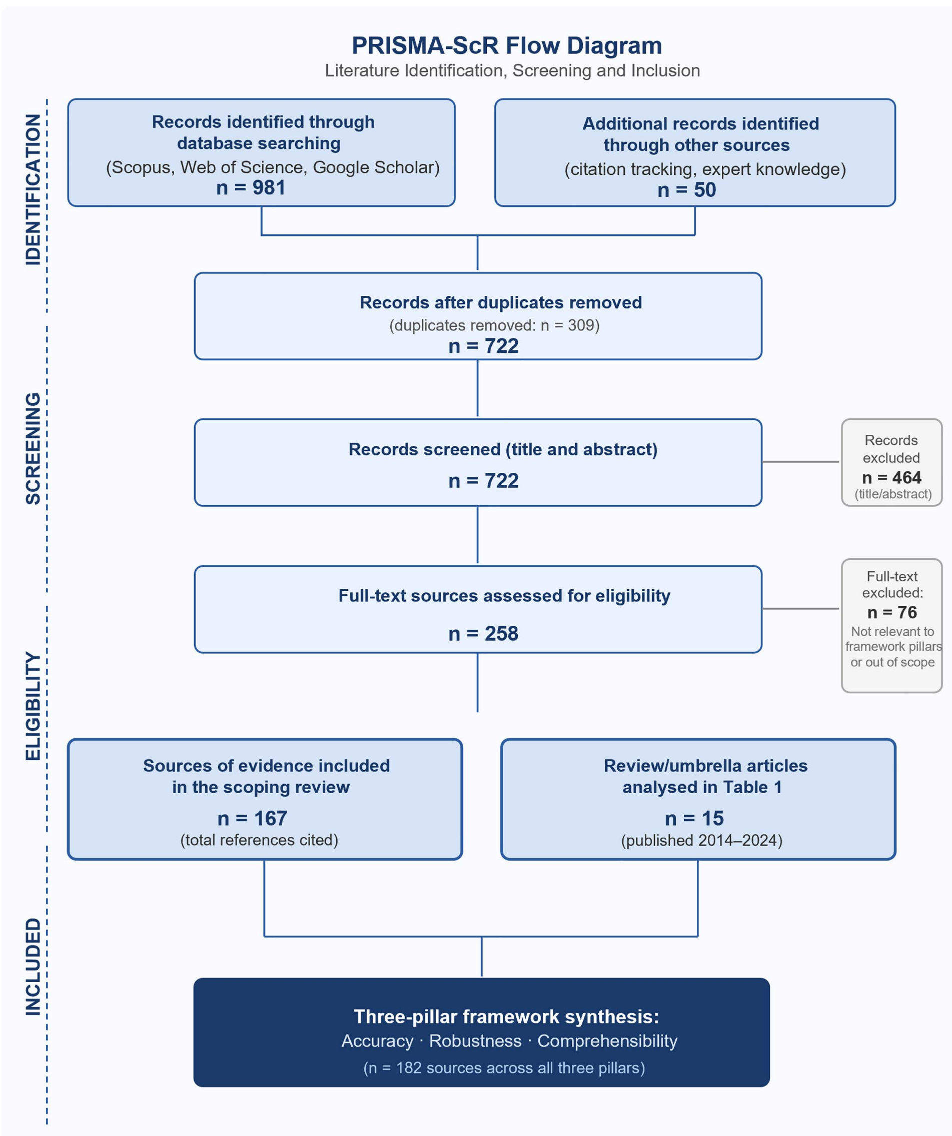

Fig 2. PRISMA-ScR flowchart.

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4.2. Highlights

- Energy modeling challenges are structured into accuracy, robustness, and comprehensibility domains
- accuracy is defined by resolution in four dimensions: time, space, techno-economic detail, and sector
- Data- and model-based uncertainty analysis strengthens modelling robustness
- Transparency, stakeholder engagement, and behavior integration enhance model comprehensibility
- Addressing these challenges allow to bridge modelling results and concrete policy implementation

Supporting information

S1 File. PRISMA Checklist.
(DOCX)

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